Policy Modelling for Sustainable Waste Management

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Chapter 5: A model for improving sustainable green waste recovery[12]

Abstract

Green waste, consisting of leaves, woodcuttings from pruning, and grass collected from parks and gardens, is a source of biomass that can be used for material and energy valorisation. Until recently, the EU-Waste Directive 2009/28/EC allowed green waste to be used as feedstock only for compost. This paper presents a framework for examining the most sustainable processing options for green waste valorisation in terms of the triple bottom line, People-Planet-Profit. A mathematical model is presented that optimizes profit, as well as environmental and social impact. Four processing options are compared and analysed: composting, partial separation of wood cuttings prior to composting, partial separation of chopped wood cuttings in the sieve overflow after composting, and a combination of the last two options. Computational results for a Belgian case demonstrate that the optimal sustainable recovery solution is to separate a fraction of the woodcuttings in the sieve overflow for use as green energy feedstock. Additionally, if sufficiently large subsidies are available to separate woodcuttings prior to composting, the optimal solution shifts to one of partially separating the cuttings both prior to composting and in the sieve overflow, and then using the combined cuttings for energy valorisation. Whenever cuttings are partially separated the remainder of the green waste is composted.

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1. Introduction

Since the Industrial Revolution, the global economy has grown rapidly through the use of mainly non-renewable raw materials as feedstock for products and energy; this has led to the depletion of non-renewable stocks. Over the last decade, this insight has been a stimulus for governments and other involved stakeholders, particularly in Western, developed countries, to begin a transition toward a sustainable society. We define sustainability in business processes as the combined economic, environmental, and social optimum of manufacturing alternatives that take into account constraints, such as technological limits or legislation, also known as the triple bottom line (TBL) approach to People-Planet-Profit optimization (Kleindorfer et al., 2005). Government regulations and legislation play an important role in this transition and in the coordination of the complex trade-offs between economic, environmental, and societal factors (Tang and Zhou, 2012). Quantitative models are rarely used to support such decisions (Seuring, 2013; Dekker et al., 2012). This paper presents a quantitative model that enables policymakers to examine different waste processing alternatives and to identify their most sustainable options, given the relative importance assigned to people, planet, and profit. Without reducing more general application, this paper proposes a sustainability assessment model for optimal green waste recovery. The proposed model can also be applied to select the optimal recovery process from a set of alternatives for other types of waste and biomass feedstock, such as food or wood waste, or lignocellulosic biomass (see e.g. Sharma et al., 2013 for an overview of conversion methods).

Green waste consists of woodcuttings from pruning (hereafter, cuttings), leaves, and grass collected after gardening. The cuttings are desirable for both composting and energy production since dry wood has an energy content of 18600 MJ/ton (McKendry, 2002). When used as co-firing in a power plant, dry wood can generate on average 1650 KWhe/ton. Until recently, green waste could be used only for compost in the EU. The current version of the EU Waste Directive 2008/98/EC (EP&C, 2008) permits separating a portion of green waste cuttings for energy recuperation if doing so can be shown to be a more sustainable option. Nevertheless composting remains the most common option to recover material from the organic fraction of municipal solid waste because of the possibility to use compost as a fertilizer (Cesaro et al., 2015).

To better explain the problem setting and the need for a quantitative model to assess sustainability effects, consider the main options for green waste material/energy recovery depicted in Figure 1. Green waste composted in open air, so-called *aerobic composting* (AC), results in compost only. It is also possible to separate some of the wooden fraction of the green waste to be used for co-firing in power plants, depicted as *"Pre-treatment"* in Figure 1. When used in Combined Heat Power (CHP) installations, the wooden mass of the green waste can produce both power and heat. The remaining fraction of the green waste can be fermented by means of an *anaerobic digestion* (AD) process, which results in biogas that can be added to a natural gas grid after upgrading. The digestate of the AD process then can be composted. The same fermentation process is also applicable for Vegetable, Fruit and Garden (VFG) waste. In many cases, co-digestion of green waste with VFG waste improves energy yield and is more economically viable (Braber, 1995).

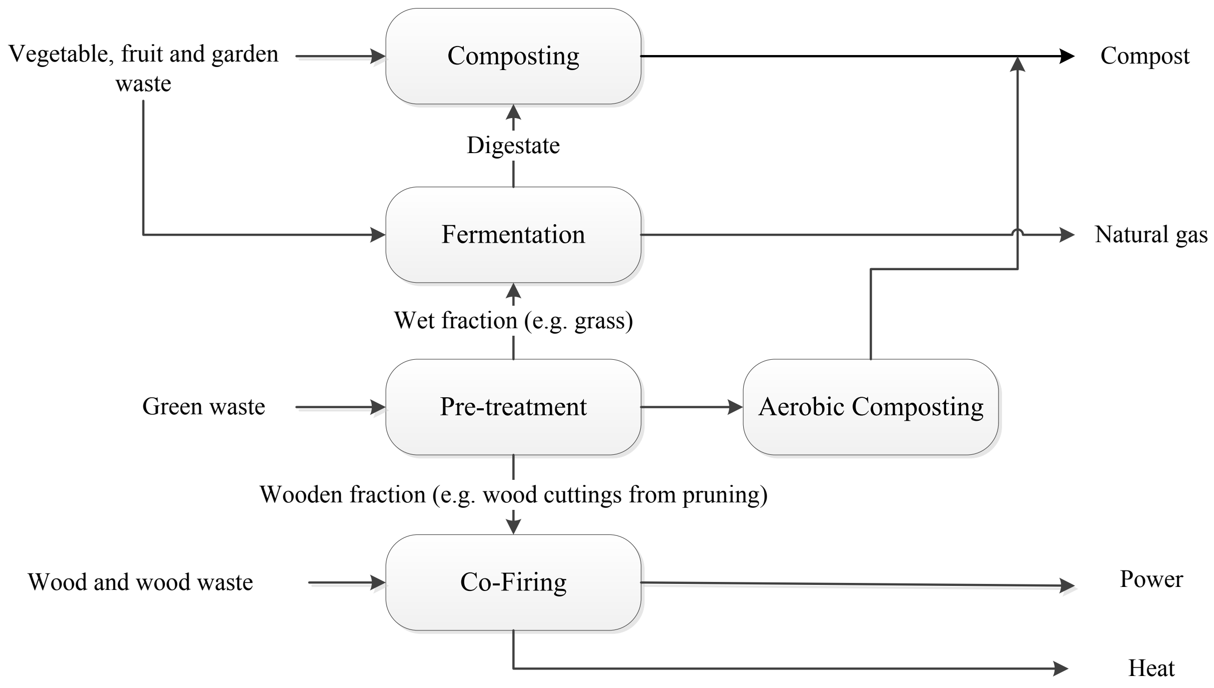

Figure 1: Alternative green waste recovery processes

Anaerobic digestion (AD) of green waste as biomass feedstock for renewable energy sources (RES) is not economically viable (Pick et al., 2012).

By using a multi-objective mathematical model, this paper will examine the sustainability of the following recovery options for processing green waste: (a) composting, (b) separation of wooden mass prior to composting, (c) separation of wooden mass after composting, and (d) separation of wooden mass prior to and after composting. The separated wooden mass can be used for co-firing in coal power plants generating power and heat.

Using a portion of green waste for energy recuperation could help EU member states, such as e.g. Belgium and the Netherlands, comply with the EU Directive 2009/28/EC (EP&C, 2009)[13] on the promotion of renewable energy resources. EU-targets for the overall share of energy from renewable sources by 2020 have already been reduced for Belgium (13%) and the Netherlands (14%), given their geographical position which results in average sunshine, average wind speed, almost no possibilities to generate hydro power, and limited biomass stocks in combination with highly dense populations. According to the latest figures of Eurostat (2015) both countries still have a huge gap to close. Additional biomass feedstocks such as green waste can help to close this gap. For this paper, we will use Flanders, the northern region of Belgium, as a case. In 2012, Flanders implemented the EU Waste Directive

[13] By 2020, so-called 20-20-20 climate targets aim to effect a 20% reduction in EU greenhouse gas emission from 1990 levels, raise the share of EU energy consumption produced from renewable resources to 20%, and improve the EU's energy efficiency by 20%.

2008/98/EC (EP&C, 2008) as part of a new Flemish waste directive VLAREMA (Flemish Government, 2012).

Vanneste et al. (2011) showed that the valorisation of wood waste in large-scale Combined Heat Power (CHP) systems and co-firing in coal plants offers the largest CO_2 reduction per TJ wood waste for Flanders. The Flemish public Waste Agency, OVAM (2009) already demonstrated the economic feasibility of partially separating cuttings from green waste if at least 15% of the cuttings could be used for energy valorisation. However, this study ignored the quantitative environmental and social impacts for the different green waste recovery alternatives examined.

Although co-firing of biomass reduces CO_2 emissions compared to regular power production (Baxter, 2005), co-firing of biomass with coal is generally more expensive than dedicated coal systems. Moreover, co-firing also has some known drawbacks such as fuel preparation, handling and storage, milling and feeding problems, different combustion behaviour, possible decreases in overall efficiency, deposit formation (slagging and fouling), agglomeration, corrosion and/or erosion, and ash utilization. The impact of these difficulties depends on the quality and percentage of biomass in the fuel blend. One of the measures to alleviate the difficulties of co-firing is the application of biomass pre-treatment used to modify biomass properties of e.g. density. The higher cost of pre-treatment needs to be evaluated against improved fuel operability (handling, storage, transportation) and operability of the boiler and combustion process (Maciejewska, 2006).

The discussion on co-firing illustrates the importance of an integrated approach towards sustainable waste valorisation. This paper does not focus on a single waste recovery process as such. Rather, it aims at selecting the waste recovery process that performs best from a triple bottom line perspective.

The remainder of this paper is as follows. Section 2 presents a literature review on sustainable value recovery and sustainability assessment modelling. Section 3 defines the problem statement. Section 4 introduces the model and Section 5 reviews the results. Finally, in Section 6 the research findings are discussed and suggestions for further research are made.

2. Literature review

Sustainable development came on the global agenda as an answer to environmental degradation, lasting poverty, and underdevelopment. The Brundtland Commission (WCED, 1987) defined sustainable development by integrating social, economic, and ecological dimensions (Hediger, 1999). As a consequence, sustainability issues are characterized by a high degree of conflicts and compromise solutions needing to be found (Munda, 2005).

Sustainability in business processes can be defined as the combined economic, environmental, and social optimum of manufacturing alternatives that take into account constraints, such as technological limits or legislation, also known as the triple bottom line (TBL) approach to People-Planet-Profit optimization (Kleindorfer et al., 2005). Many sustainability assessments are built on the TBL concept (Seuring, 2013), which refers to the accountancy concept that extends classical financial reporting to include social and environmental performance reporting, as proposed by Elkington (1994).

The TBL framework requires all three dimensions to be quantified. The economic pillar is commonly represented by the minimization of costs or the maximization of profits (Seuring and Müller, 2008). However, since the World Summit on Sustainable Development in Johannesburg in 2002, prosperity is also used, instead of profit, to reflect the perspective that the economic dimension covers more than company profits (Heijungs et al., 2010). For the environmental pillar the standard assessment tool is the Life Cycle Assessment (LCA), described by ISO 14040 +44 (2006). Additionally, the Eco-indicator methodology (Goedkoop and Spriensma, 2001) can be applied to quantify environmental impacts in a simplified manner. As economic and environmental dimensions have been on the agenda for some time, there is a growing consensus on how to describe them (Seuring and Müller, 2008) and a number of (optimization) models can be found in the academic literature. A commonly accepted definition for the social dimension is not yet available, largely because there is not yet consensus on the meaning of the term 'social' (Lehtonen, 2004). The social dimension is immaterial and therefore difficult to analyse quantitatively (Lethonen, 2004; Munda, 2004). Since many social indicators cannot be quantified, qualitative ranking and scoring is currently used alongside quantitative measures (Klöpffer, 2008). A popular method from Multi-Criteria Decision Making (MCDM) that can be used to quantify such qualitative comparisons is the Analytic Hierarchy Process, (AHP) (Saaty, 2008). AHP requires the social criteria of interest to be selected and rated by means of pair-wise comparisons, as illustrated in Dehghanian and Mansour (2009), which utilized AHP to compare social impacts for several design options to obtain a sustainable recovery network for end-of-life tires in Iran.

Seuring (2013) concludes that only a limited number of papers on green or sustainable (forward) supply chains apply quantitative models. Moreover, the social aspect of sustainability is often ignored in these quantitative models. As such, Seuring (2013) asserts that the conclusions of an earlier extensive literature review of 191 papers on sustainable supply chain management (Seuring and Müller, 2008) are still valid. The earlier literature review showed that all papers covered the economic dimension, 140 also covered the environmental dimensions (for waste see e.g. Vadenbo et al., 2014), but only 20 covered the social dimension. These findings are in line with Sharma et al. (2013), which reviewed 32 papers dealing with biomass supply chains and observed that only two papers used multi-objective programming models to optimize simultaneously the economic, social and environmental objectives.

Currently various methodologies and frameworks are available for assessing sustainability at different levels such as e.g., country, city, and organization (Moldavska and Welo, 2016). Following Munda (2005) we consider Multiple Criteria Analysis (MCA) to be a suitable tool for assessing sustainability of green waste recovery. Because the economic, environmental, and social dimensions of the different recovery options are difficult to impossible to compare, Multiple Criteria Analysis evaluation offers the appropriate methodological tools to operationalize the concept of incommensurability at both macro and micro levels of analysis (Munda, 2005; Martinez-Alier et al., 1998).

MCA is formed upon the premise that there are many and, at times, conflicting economic, environmental and social preferences, but that a consensus should be sought (Oglethorpe, 2010). According to the stakeholders' view, the importance of each objective, related to the three dimensions to be optimized, can be varied by assigning weight factors (Carter & Rogers, 2008; Oglethorpe, 2010). Oglethorpe (2010) uses goal programming to optimize the three pillars and focuses on costs, on-time delivery, lead time, GHG emitted, energy used, water used, health impacts and number of accrued jobs. You et al. (2011) uses the ε-constraint method to solve the multi-objective mixed-integer linear programming model that optimizes the three sustainability pillars. They focus on costs, on time delivery, lead-time, food quality degraded, food waste, GHG emitted, water used, and number of accrued jobs. Another approach is presented by Dehghanian and Mansour (2009), who use a multi-objective genetic algorithm (MOGA) to find Pareto-optimal solutions for designing a sustainable recovery network, in which economic, environmental, and social impacts are balanced. Devika et al. (2014) conclude that a gap still exists in the quantitative modelling of social impacts alongside environmental and economic impacts. They develop a mixed-integer programming (MIP) model which uses hybrid metaheuristic methods to solve multi-objective closed-loop supply chain network problems, taking the three sustainability pillars into account. And Mota et al. (2015) describe a multi-objective mixed-integer linear programming (MOMILP) model for the design and planning of sustainable closed-loop supply chains. Their objectives include profit optimization (NPV), environmental impact minimization using the LCA methodology ReCiPe, and socio-economic indicators applied by the European Union in its Sustainable Development Strategy.

The previous mentioned papers demonstrate how the three sustainability pillars can be integrated in a mathematical model. They present extendable alternative approaches for the inclusion of the societal "people" pillar of sustainability. However, these papers are exceptions to the rule: most models to assess sustainable outcomes deal with a combined economic and environmental optimization only.

In this paper we want to formulate a multiple-objective mixed-integer linear programming (MOMILP) model with three objective functions (economic, environmental, and social) for green waste recovery. The model is applied to a case in Flanders, introduced in the next section. Since we compare the traditional composting option with other options that may require additional investments, it is appropriate to calculate the Net Present Value of the differences to the current situation (see e.g. Guillen-Gosalbez and Grossmann, 2010). To assess the environmental aspects of the different options, we use the commonly used LCA methodology. Since green waste is not intentionally grown, but is a by-product, it is not suitable to use a complete life-cycle approach in which the closed-loop supply chain must be evaluated (Grant, 2003). Instead, the process can be better evaluated on its own as a gate-to-gate process in which only the waste treatment is considered. If green waste is delivered to the processing facility, then the waste treatment process to obtain compost and separate the wooden mass also needs to be considered. To assess the social impact, we utilize AHP to compare the different scenarios for green waste valorisation, following Dehghanian and Mansour (2009).

3. Problem statement and analysis

The composition of green waste differs for each season (e.g. less grass and leaves in winter) and for each geographical location (VLACO, 2010). Since no typical composition of green waste for Flanders is available, the typical composition in the Netherlands (SenterNovem, 2008) is used in our case study for Flanders. Green waste in the Netherlands can be assumed to have the same composition as in Flanders, the northern part of Belgium, which is situated next to the Netherlands. Dutch green waste has a moisture content of 50%, an ash content of 20%, and a caloric value of 6.4 MJ/kg (SenterNovem, 2008). The wooden fraction of the green waste can be divided into three subcategories: small (<20 mm), medium (20-80 mm), and large (>80 mm). The compost is sieved at the end of the composting process. The wooden fraction that passes through the sieve with a mesh-size of 20 mm stays in the compost. The remainder is called the sieve overflow and can be reused as structural material in the compost process, or separated for energy valorisation.

Figure 2 represents the various options for the recovery of green waste embedded in the current aerobic composting process under study. It represents the generic mass balance in weight percentage of the incoming green waste, in an instance in which all green waste is composted. The typical mass input of a batch of green waste is composed of 50% grass, 30% sieve overflow (a remainder of the previous composting run), and 20% mass of fresh cuttings. This leads to a typical mass output of 40% compost, 30% sieve overflow, and 30% emissions such as water, gasses and pollutants as reported by OVAM (2009).

The aim of this paper is to assess whether separating sieve overflow and/or fresh cuttings from a batch of green waste can be more sustainable than composting green waste exclusively. Therefore, we need to quantify the relationship between the composition of the blend (grass, fresh cuttings, and sieve overflow) and compost. According to compost practitioners, separating part of the fresh cuttings in a green waste batch, and/or those from its sieve overflow, will lead to a reduction in the amount of compost being produced (OVAM, 2009). In order to quantify this effect we examine the best available data. VLACO (2010), The Flemish Agency for Compost (2010) reports on experiments in two different plants that can be used to gain a preliminary insight in this process. The estimation of the mass of compost based on the mass explanatory variables of grass, fresh cuttings, and sieve overflow calls for a careful interpretation since only a small number of observations are available. Therefore we will also take into account the compost practitioners' expected effects of partially separating fresh cuttings and sieve overflow on the compost yield of a batch of green waste.

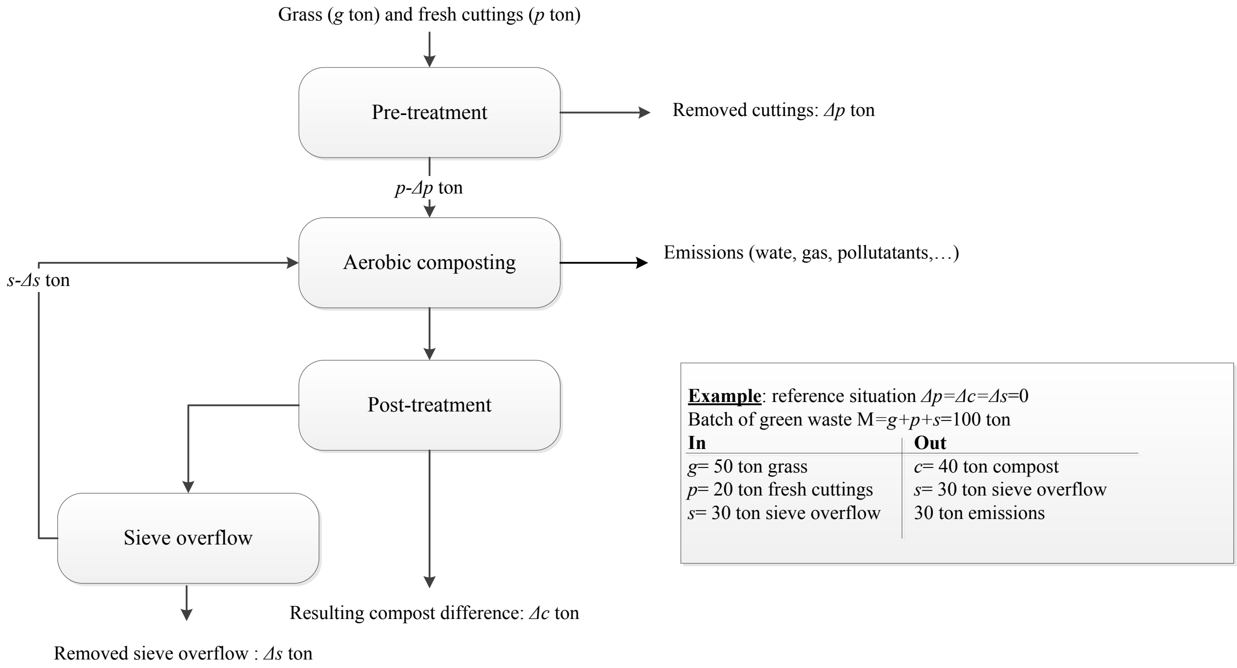

Figure 2: Overview aerobic composting process with possible separation of fresh cuttings and sieve overflow for energy valorisation

In the first (summertime) experiment of VLACO (2010), the impact of the amount of grass, fresh cuttings, and sieve overflow on compost output was examined for four batches of 350-ton green waste input, each with a differing composition. The sieve overflow contained grinded cuttings with a diameter ranging between 15 and 40 mm.

Let:

p: amount of fresh wood cuttings (from pruning) in a batch of green waste [ton]
s: amount of sieve overflow in a batch of green waste [ton]
g: amount of grass in a batch of green waste [ton]
c: resulting amount of compost [ton]

	Input (per 100 ton green waste)			Output
Batch	Grass, *g* [ton]	Fresh cuttings, *p* [ton]	Sieve overflow, *s* [ton]	Compost, *c* [ton]
1	44	20	36	28
2	47	18	35	35
3	56	26	18	25
4	68	14	18	19

Table 1: Influence of the composition of green waste on the mass output of compost (based on VLACO, 2010)

The results in Table 1 show that a batch consisting of about 50% grass and 50% fresh cuttings plus sieve overflow yields the highest green waste output of compost. Deviations from this green waste composition seem to lead to less compost, based on a limited number of test batches.

Using the limited number of observations in Table 1, the yield of compost, c, is estimated using a multiple linear regression analysis on the predictors grass, g, fresh cuttings from pruning, p, and sieve overflow, s, and the observed responses of the resulting amount of compost, c, on four observations. Following OVAM (2009), a linear relationship may be assumed. The resulting estimated amount of compost $\hat{c}$ is expressed by Eq. 1, which is obtained by using Matlab R2014b.

$$\hat{c} = 0.046 \cdot g + 0.427 \cdot p + 0.597 \cdot s \qquad R^2 = 0.732; R^2_{adj} = 0.195; p - \text{value} = 0.518 \tag{1}$$

As we want to quantify the effect of separating fresh cuttings and/or sieve overflow on the resulting amount of compost, as compared to the reference situation of exclusive composting, we express the variables in Eq. 1 as differences between exclusive composting and the remaining amount after separating cuttings, grass and/or sieve overflow. This is based on the fact that Eq. 1 holds true for any difference Δp, Δs and Δg of two different batches expressed in Table 1.

Let:

$$\Delta p = p_{ref} - p_{remaining} \tag{2}$$

$$\Delta s = s_{ref} - s_{remaining} \tag{3}$$

$$\Delta g = g_{ref} - g_{remaining} \tag{4}$$

$$\Delta\hat{c} = c_{ref} - c_{remaining} \tag{5}$$

Eq. 1 can be expressed in terms of the differences expressed in Eq.2-5, see Eq. 6:

$$\Delta\hat{c} = 0.046 \cdot \Delta g + 0.427 \cdot \Delta p + 0.597 \cdot \Delta s \tag{6}$$

For any two different batch observations in Table 1, the sum of the mass differences equals zero as expressed in Eq. 7

$$\Delta g + \Delta p + \Delta s = 0 \tag{7}$$

This allows expressing the estimated compost difference $\Delta\hat{c}$ as a function of only Δp and Δs

$$\Delta\hat{c} = 0.381 \cdot \Delta p + 0.551 \cdot \Delta s \tag{8}$$

Based on the limited number of experiments of VLACO (2010), Eq. 8 indicates that the separation of fresh cuttings has less influence on the resulting amount of compost than the separation of sieve overflow. This finding is challenged, however, by a subsequent experiment of VLACO (2010).

The second experiment from VLACO (2010), investigated the influence on the compost yield of using cuttings with a diameter larger than 20 mm in a green waste batch. Each season, the incoming green waste was grinded, mixed, and sieved with a mesh size of 20 mm. Cuttings with a diameter larger than or equal to 20 mm were set aside. Next, the waste mixture was divided in two and cuttings with a diameter larger than 20 mm were reintroduced to one of the two parts. The subsequent batches created from this mixture containing sieved wooden mass larger than 20 mm are denoted with "+". The other mixed green waste batches, created from a mixture not containing sieved wooden mass larger than 20 mm, are denoted with "-". None of the batches contained a portion of the sieve overflow. The process of composting lasted 10 to 12 weeks. All batches were treated equally during compost processing. After composting, the input mass of both types of batches was sieved with a mesh size of 12 mm. The results are listed in Table 2.

Batch	Composition Green Waste (per 100 ton)		Compost (ton)	Compost yield y (weight compost output/ weight green waste mixture with fine material < 20 mm) in [%]
	Weight fine cuttings dia ≤ 20 mm	Weight medium and large cuttings dia > 20 mm		
1+	61	39	55	90.16
2+	52	48	43	82.69
3+	49	51	48	97.96
4+	51	49	49	96.08
1-	59	0	45	76.27
2-	49	0	32	65.30
3-	51	0	48	94.12
4-	46	0	46	100.00

Table 2: Influence of wooden input material on compost (data based on experiments VLACO, 2010)

Using the data in Table 2, we analyse, per season, the impact on the compost yield y of the presence of wooden mass with diameter larger than 20 mm in the green waste input. The mean of the compost yield of the batches with wooden mass with a diameter larger than 20 mm, $\bar{y}_1$, is compared to the mean of the compost yield of the batches without it, $\bar{y}_2$ (see Table 3). The verification is carried out with a significance level α =0.05 on the difference between the two means with the test statistic t_0^* (Montgomery & Runger, 1999) on the null hypothesis $H_0 : \bar{y}_1 = \bar{y}_2$. The null hypothesis cannot be rejected at the 5% significance level (p-value = 0.6250).

Composting with wooden mass with diameter > 20 mm	n_1=4	$\bar{y}_1 = 91.72\%$	$s_1 = 6.88$
Composting without wooden mass with diameter > 20 mm	n_2=4	$\bar{y}_2 = 83.92\%$	$s_2 = 16.00$

Table 3: Effect of wooden mass with diameter larger than 20 mm on the compost yield of green waste

In conclusion, in the case of a regular composition of green waste (i.e. about 50% green and 50% wooden mass), the effect of separating medium and large cuttings with a diameter > 20 mm during pre-treatment has no significant effect on the mean compost yield.

Since the above described analysis was based on a very limited number of observations, the results are taken with caution and compared with the compost practitioners' (OVAM, 2009) expected effects—that by taking a portion of sieve overflow Δs out of the green waste input, the resulting difference in the amount of compost, $\Delta\tilde{c}$, would decrease by 50% of Δs. Furthermore, practitioners intuitively expect that taking out a portion of fresh cuttings Δp in the green waste input would reduce the expected resulting amount of compost difference with 10% of Δp. The expected resulting amount of compost difference $\Delta\tilde{c}$ based on the compost practitioners' experience is expressed in Eq. 9

$$\Delta\tilde{c} = 0.1 \cdot \Delta p + 0.5 \cdot \Delta s \tag{9}$$

As outlined in the introduction, our goal is to investigate whether, during a pre-treatment of the green waste input, separating a part of the wooden mass of the sieve overflow after composting or prior to the start of the compost process will enhance the sustainable recovery of green waste. Four feasible alternatives are examined. These alternatives denoted $\alpha_1 ... \alpha_4$ are summarized in Table 4.

Alternative *k*	**Description**	**Sieve overflow separated after composting**	**Fresh cuttings separated during pre-treatment**	**Change in mass balance compared to the reference situation of exclusive green waste composting.**
α_1	Exclusive composting (reference scenario)	☒	☒	$\Delta s = \Delta p = \Delta\hat{c} = \Delta\tilde{c} = 0$
α_2	Only sieve overflow	☑	☒	$\Delta\hat{c} = 0.551 \cdot \Delta s; \Delta p = 0$ $\Delta\tilde{c} = 0.5 \cdot \Delta s; \Delta p = 0$
α_3	Pre-treatment & sieve overflow	☑	☑	$\Delta\hat{c} = 0.381 \cdot \Delta p + 0.551 \cdot \Delta s$ $\Delta\tilde{c} = 0.1 \cdot \Delta p + 0.5 \cdot \Delta s = 0$
α_4	Only pre-treatment	☒	☑	$\Delta\hat{c} = 0.381 \cdot \Delta p; \Delta s = 0$ $\Delta\tilde{c} = 0.1 \cdot \Delta p; \Delta s = 0$

Table 4: Overview of the four alternatives to be considered for the valorisation of green waste

As outlined in the introduction, the EU Waste Directive 2008/98/EC (EP&C, 2008) now permits diverting green waste from the exclusive use of composting if an alternative use is proven to yield a more sustainable outcome. Section 4 presents and discusses a model capable of selecting the most sustainable alternative from a set of alternatives.

4. Model development

The goal of this section is to develop a framework for assessing the sustainable value recovery of green waste given the options for composting and wood extraction prior to and/or after composting.

4.1. Sustainability Assessment

Profit

Since profit is the only consideration when comparing value recovery alternatives, the objective function can be formulated as the maximization of the Net Present Value (NPV) of different investment options (challenger situations) as compared to the actual situation (defender situation). In this equation, any difference in cash flow, CF_t, between the defender situation and the k challenger alternatives, needs to be taken into account.

$$\max\left[-FCI_k+\sum_{t=1}^{n}\frac{CF_t}{(1+i)^t}\right] \tag{10}$$

The Net Fixed Capital Investment, FCI_k, is the investment needed for a different conversion alternative k than the defender situation, taking potential subsidies into account. The number of annual interest periods is represented by n. The annual interest rate is denoted by i [%]. Since the investment takes place in period 0, t starts from t=1.

When the cash flows CF_t are constant and equal to an amount B paid at the end of each annual interest period, the right hand side of equation (10) can be rewritten as (Thuesen and Fabrycky, 1993):

$$\sum_{t=1}^{n}\frac{CF_t}{(1+i)^t}=B\cdot\left[\frac{(1+i)^n-1}{i\cdot(1+i)^n}\right] \tag{11}$$

Planet

The environmental impact of products and processes is commonly assessed by means of an LCA that takes all environmental issues and their impacts into account across the entire life cycle (production, use, end of life). The environmental impact of each alternative k is expressed as EI_k. Examples based on the scientific CML process (see http://www.cml.leiden.edu) are the Global Warming Impact expressed in [kgCO_2/kg], the depletion potential of the stratospheric ozone layer (ODP), the summer smog creation potential (POCP), the acidification potential of soils and water bodies (AP), the nitrification potential of soils and water bodies (NP), and the depletion of abiotic resources (ADP). Other internationally accepted impact assessment methodologies are eco-indicator 99, IMPACT 2002+, ReCiPe, TRACI I, and EDIP.

People

To quantify the relative social impact of the four alternatives listed in Table 4, we use AHP (Saaty, 2008). First, social impact criteria (e.g. safety, employment, etc.) need to be defined. Second, relative priority levels for the l selected criteria need to be determined by assigning normalized weighting factors ω_l to each. These weighting factors will not differ for the four alternatives under study. Third, for each criterion, the normalized weight factors ω_{lk} for social impact criterion l on alternative k are derived. The relative weight of each criterion l per alternative k is used to determine the social impact for each alternative k. The higher the impact score, the more social importance is linked to that alternative.

4.2. Mathematical formulation

The most sustainable alternative for green waste recovery out of the k alternatives is determined by simultaneously optimizing the three objectives describing the TBL. The sustainable optimum of green waste recovery encompasses economic and social benefits maximization and environmental impact minimization, as described above. This can be expressed mathematically by a multi-objective programming model with three objective functions (12)-(14) subject to constraints (15)-(23).

The following decision variables are used:

Δp: mass of fresh cuttings separated during pre-treatment compared with the defender situation [ton]
Δs: mass of sieve overflow separated after composting compared with the defender situation [ton]
Δc: change in amount of compost compared with the defender situation [ton]
α_k: investment alternative k (α_k=1 if alternative k is selected, otherwise α_k=0)

The parameters and indices used are:

FCI_k: net Fixed Capital Investment for alternative k taking potential subsidies into account [€]
n: number of annual interest periods
i: annual interest rate [%]
CF_p: Fixed yearly cash flow per ton for the fraction separated fresh cuttings Δp [€/ton]
CF_s: Fixed yearly cash flow per ton for the fraction separated sieve overflow Δs [€/ton]
CF_c: Fixed yearly cash flow per ton for the fraction separated compost Δc [€/ton]
CF_g: Fixed yearly cash flow per ton for the fraction separated grass Δ g [€/ton]
M: Mass of green waste input per year in the recovery facility [ton]
EI_m: Environmental Impact of process treatment for the part m in the green waste batch ($m=s$ for sieve overflow, $m=p$ for pre-treatment, $m=g$ for grass and $m=c$ for compost)
ω_l: normalized weight factor for social impact criterion l

ω_{lk}: weight factor for social impact criterion l on alternative k

The model consists of three objective functions Z_1, Z_2 and Z_3 subject to constraints (15) to (23):

$$\max Z_1 = \left[-FCI_k + (CF_s \cdot \Delta s + CF_p \cdot \Delta p + CF_g \cdot \Delta g + CF_c \cdot \Delta c \cdot \frac{(1+i)^n - 1}{i \cdot (1+i)^n} \right] \tag{12}$$

$$\min Z_2 = \Delta s \cdot EI_s + \Delta p \cdot EI_p + \Delta g \cdot EI_g + \Delta c \cdot EI_c \tag{13}$$

$$\max Z_3 = \sum_{l=1}^{l} \sum_{k=1}^{k} \omega_l \cdot \omega_{lk} \cdot \alpha_k \tag{14}$$

Subject to:

$$f(\Delta s, \Delta p, \Delta g, \Delta c) = 0 \tag{15}$$

$$s_{\min} \le \Delta s \le s_{\max} \tag{16}$$

$$p_{\min} \le \Delta p \le p_{\max} \tag{17}$$

$$g_{\min} \le \Delta g \le g_{\max} \tag{18}$$

$$c_{\min} \le \Delta c \le c_{\max} \tag{19}$$

$$\Delta s, \Delta p \ge 0 \tag{20}$$

$$\Delta c \le 0 \tag{21}$$

$$\sum_{k=1}^{k} \alpha_k = 1 \tag{22}$$

$$\alpha_k \in \{0,1\} \tag{23}$$

This model maximizes simultaneously the cash flow (12) and social impact (14) and minimizes the environmental impact (13). The mass balance reflecting the effect of separating the portions Δs, Δp, Δg on the resulting amount of compost Δc is expressed in (15). This effect will differ if observed or expected data are used as already shown in Eq. 8 and Eq. 9, respectively. Constraints (16)-(18) reflect the boundaries of separating the fractions Δs, Δp, Δg in the green waste batch. The allowed compost loss due to separation of fresh cuttings and/or sieve overflow is expressed in constraint (19). Constraint (20) expresses that we consider only those situations in which we separate fresh cuttings and/or sieve overflow in a batch of green waste composed of 50% grass and 50% cuttings and sieve overflow, and which yield the maximum resulting amount of compost. Therefore, every separation of fresh cuttings and sieve overflow will result in a decrease in the resulting amount of compost difference, expressed by a non-positive amount Δc (21). The green waste recovery alternatives are mutually exclusive (22). The variable for the alternatives k, α_k, is a binary variable (23).

The next step is to quantify the objective functions (12)-(14) and the constraints (15)-(23) for the case described in section 3. This is discussed in the next section.

5. Computational results

In this section, the model from Section 4 is applied to a practical case of Flanders for a green waste facility that deals with 25,000 tons of green waste per year. In this case, fresh cuttings and sieve overflow are separated, as compared to the reference situation of composting only (i.e. Δg=0), and lead to a loss of compost.

5.1. Profit objective function

The costs and benefits linked to the various alternatives listed in Table 4 are presented in Table 5.

	Investment in additional equipment [€]	Variable cost [€/ton final product]	Revenue [€/ton final product]	Benefit [€/ton final product]
Compost	0		5	5
Biomass retrieved from sieve overflow	0	2	6.5	4.5
Biomass retrieved from pre-treatment	200,000	2	11	9

Table 5: Overview of cash flow parameters for the different alternatives (data based on OVAM (2009)

Taking into account expression (12) and Table 5, Z_1 is expressed as

$$Z_1 = -200{,}000 \cdot (\alpha_3 + \alpha_4) + (9 \cdot \Delta p + 5 \cdot \Delta c + 4.5 \cdot \Delta s) \cdot \frac{(1+i)^n - 1}{i \cdot (1+i)^n} \tag{24}$$

Following OVAM (2009) we will impose an annual interest or return rate of 7% for the different options over a period of 5 years, resulting in expression (25)

$$Z_1 = -200{,}000 \cdot (\alpha_3 + \alpha_4) + 36.9 \cdot \Delta p + 20.5 \cdot \Delta c + 18.45 \cdot \Delta s \tag{25}$$

5.2. Environmental objective function

Since no LCA study has been carried out on the different components in Flanders, we use the LCA analysis that was carried out by SenterNovem (2008) for one ton of Dutch green waste. This study of a biomass power plant compares the environmental impact of composting of green waste to incineration with energy recuperation of the same composition of green waste. The LCA took the following aspects into account: the composition of the green waste, the energy consumption of all the processes involved, and the (avoided) emissions to air, ground water and soil. Using SimaPro 6.02 SenterNovem (2008) calculated the environmental impact scores on the total emissions to the environment, depletion of raw materials, and space. Comparing them with the total environmental impact of the Netherlands normalized these environmental impact scores. This resulted in weighted environmental impact scores, further noted as Environmental Impact *EI*. Environmental impacts can be expressed in LCA points (abbreviated as "*Pt*") that relate to a ton of green waste that is either composted or incinerated with energy recuperation. The higher the score, the higher is the negative impact on the environment. A negative impact score reflects the avoidance of environmental impact.

The environmental objective function (13) takes into account the environmental impact of composting and the retrieval of fresh cuttings during pre-treatment, or retrieval from the sieve overflow for co-firing in an energy plant. This impact is reflected in a normalized environmental effect score (points).

If all the aspects of the LCA analysis are weighted equally, the environmental impact score of one ton of composted green waste can be represented by -1537 points denoted as -1537 Pt/ton and one ton of the same green waste composition with a caloric value of 6.4 MJ/kg (SenterNovem, 2008), incinerated with energy recuperation, can be denoted as -5374 Pt/ton. Since a lower number represents a lower environmental impact, this signifies that the latter option has a better environmental impact solution.

In the case described in this paper, we only intend to incinerate a portion of the wooden fraction of the green waste input and a portion of the sieve overflow. The wooden fraction in the green waste input has a caloric value of 8MJ/kg (OVAM, 2009) and a moisture content of 50%. The sieve overflow has more impurities and a lower caloric value. The exact caloric value is not publically available, but we assume the value of both wooden masses to be proportional to their market value as depicted in table 5. Hence the caloric value of sieve overflow is assumed to be equal to: 6.5/11 * 8MJ/kg = 4.7 MJ/kg by allocation.

Since the energy recuperation is the most influential parameter in the environmental impact score, we derive the LCA scores for the wooden fraction of green waste and for the sieve overflow based on the caloric values as follows:

Wooden fraction: 8/6.4 * (-5374) = -6717 Pt/ton and
Sieve overflow: 4.7/6.4 * (-5374) = -3947 Pt/ton.

Z_2 can now be expressed as:

$$Z_2 = 25{,}000 \cdot (-6{,}717 \cdot \Delta p - 1{,}537 \cdot \Delta \widehat{c} - 3{,}947 \cdot \Delta s) \quad (26)$$

5.3. Social Impact objective function

For quantifying the social impact, we use AHP (Saaty, 2008). The social impact objective function (14) is the final outcome of the AHP assessment that assigns a social impact factor to the four alternatives under investigation. The alternative with the highest social impact factor is the most sustainable from the point of view of the social impact objective. First, criteria must be chosen that are representative for assessing the Social Impact of the four alternatives (Figure 3): safety, local employment, job enrichment and job security were selected as criteria.

These criteria then need to be pair-wise ranked by relative importance on a scale ranging from 1 to 9. The higher the number, the higher is the importance. For this case study the relative importance of the relative importance comparison of the social impact criteria were scored as following (SA:LE) = (5:1), (SA:JV) =(9:1), (SA:JS)=(7:1), (LE:JV) = (7:1), (LE:JS)=(3:1), (JV:JS) = (1:3)

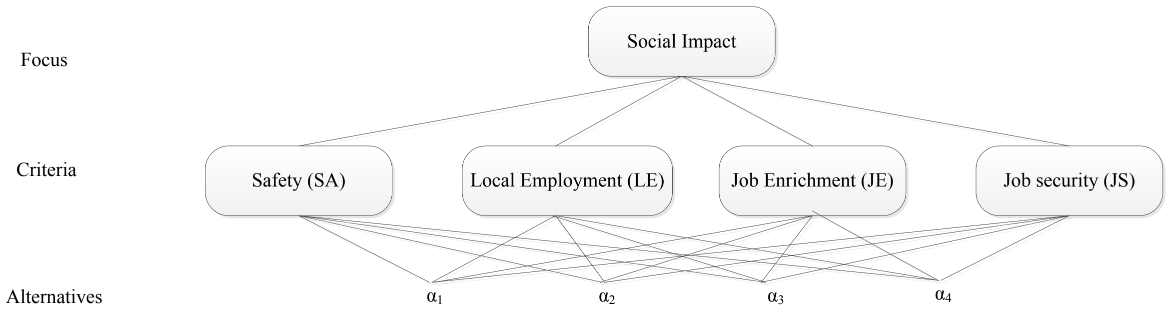

Figure 3: Focus, Criteria and Alternatives used in the AHP approach to assess the Social Impact for the four investment alternatives for the valorisation of green waste

The pair-wise comparison assessment of the social impact criteria are then put into a comparison matrix *A* whose element at row *i* and column *j* is the ratio of row *i* and column *j*. The first row compares, from left to right, the criteria S, LE, JV and JS with the elements in the first column that run, from top to bottom, SA, LE, JV and JS. For example element a_{ij} = a_{32}=LE/JV = 7. For this case study the comparison matrix *A* is denoted in (27):

$$A = \begin{bmatrix} 1 & 5 & 9 & 7 \\ 1/5 & 1 & 7 & 3 \\ 1/9 & 1/7 & 1 & 1/3 \\ 1/7 & 1/3 & 3 & 1 \end{bmatrix} \tag{27}$$

Since in general this pair-wise comparison of priorities by decision makers is not consistent, by definition, AHP allows some inconsistency. The level of (in)consistency is checked by the calculation of the consistency ratio. The consistency ratio is computed from the eigenvalue λ_{max} of the comparison matrix. Saaty (2006) defines the consistency index, *CI*, as a measure of consistency

$$CI = \frac{\lambda_{\max} - l}{l - 1} \tag{28}$$

with l = number of criteria and λ_{max} the largest eigenvalue of *A*.

For the case study λ_{max} = 4.205, l = 4 and consequently *CI* = 0.068.

Finally, the CI is compared to a value derived by generating random reciprocal matrices of the same size to give a consistency ratio CR. The comparative values, CV, are dependent to the size of the criteria comparison matrix

$$CR = \frac{CI}{CV} \tag{29}$$

In this case of a 4x4 matrix A, the CV = 0.89 (Saaty, 2006). For the case study CR = 0.077 <0.1 and is, therefore, determined to be acceptable (Saaty, 2006).

The next step is the pair-wise comparison of the four alternatives α_k on the four criteria. Table 6 summarizes the relative priority level for each criterion of the alternatives. In the above row, the normalized weighting factors ω_l are listed between brackets for each criterion. For example, safety (S) has a normalized weighting factor of 0.65. Per criterion, the normalized weight factors ω_{lk} for social impact criterion l on alternative k are listed in each column.

Finally, AHP computes the contribution of each alternative to the overall goal (see Eq. 14). For example, the Social Impact of alternative α_2 is calculated as $Z_{3,\alpha 2}$ = (0.65)·(0.16) + (0.22)·(0.08) + (0.04)·(0.12) + (50.09)·(0.12) = 0.14

Normalized weight factors ω_{lk}	**Criteria l (ω_l listed between brackets for each criterion)**			
Alternative k	SA(0.65)	LE(0.22)	JV(0.04)	JS(0.09)
α_1	0.35	0.08	0.16	0.16
α_2	0.16	0.08	0.12	0.12
α_3	0.18	0.42	0.52	0.52
α_4	0.31	0.42	0.20	0.20

Table 6: Summary priorities for each hierarchical level

Z_3 in (14) can now be expressed as:

$$Z_3 = 0.27\alpha_1 + 0.14\alpha_2 + 0.28\alpha_3 + 0.32\alpha_4 \tag{30}$$

5.4. Constraints

For the observed data, Eq. 8 expresses the mass balance of Eq. 15. Furthermore the compost difference $\Delta \hat{c}$ will be expressed by a negative number (see Eq. 21):

$$0.381 \cdot \Delta p + \Delta \hat{c} + 0.551 \cdot \Delta s = 0 \tag{31}$$

Along the same lines, the mass balance involving the expected compost yield expressed in Eq. 9 can be written as:

$$0.1\Delta p + \Delta \hat{c} + 0.5 \cdot \Delta s = 0 \tag{32}$$

According to OVAM (2009) sieve overflow accounting for at most 15% of the green waste batch of M ton can be separated without hampering the composting process. This upper limit is reduced by 50% if a portion of the fresh cuttings is also separated, which is only applicable for alternative α_4

$$\Delta s + 0.075 \cdot M \cdot \alpha_4 \leq 0.15 \cdot M \tag{33}$$

To avoid hampering the composting process, the fraction of fresh cuttings that may be separated during pre-treatment is limited to 20% of the green waste batch of M ton:

$$\Delta p - 0.2 \cdot \alpha_3 \cdot M - 0.2 \cdot \alpha_4 \cdot M \leq 0 \tag{34}$$

The allowable compost reduction due to the separation of sieve overflow and/or the wooden fraction is limited to 10% of the green waste batch of M ton (OVAM, 2009):

$$\Delta \hat{c} + 0.1 \cdot \alpha_2 \cdot M + 0.1 \cdot \alpha_3 \cdot M + 0.1 \cdot \alpha_4 \cdot M \geq 0 \tag{35}$$

Sieve overflow can be separated only if the alternatives α_2 or α_3 are selected

$$\Delta s - M \cdot \alpha_2 - M \cdot \alpha_3 \leq 0 \tag{36}$$

We consider cases only where sieve overflow and fresh cuttings may be separated

$$\Delta s, \Delta p \geq 0 \tag{37}$$

Since we are making a comparison with the reference situation of exclusively composting with an optimal mix, separating fresh cuttings and/or sieve overflow will lead to a reduction in compost. Hence the reduction of compost is expressed as a negative number

$$\Delta \hat{c}, \Delta \tilde{c} \leq 0 \tag{38}$$

The alternatives are represented as binary variables

$$\alpha_k \in \{0,1\}; k \in \{1,2,3,4\} \tag{39}$$

All alternatives are mutually exclusive

$$\sum_{k=1}^{4} \alpha_k = 1 \tag{40}$$

The MOMILP for the green waste case with objectives (25), (26) and (30) and constraints (31)-(40) was solved using the augmented ε constraint method (AUGMECON), a new version of the conventional ε-constraint method that provides remedies for its well-known pitfalls (Mavrotas, 2009). In the ε-constraint method, one of the objective functions is optimized while the other objective functions are used as constraints. It has several advantages over the weighting method (Mavrotas, 2009), such as obtaining a richer representation of the Pareto optimal front and being fit for use in multi-objective integer and mixed-integer programming problems. Compared to the ε-constraint method, the AUGMECON method avoids generating weak Pareto optimal solutions and accelerates the optimization process by avoiding redundant solutions. The AUGMECON method is available in a number of different modelling languages, including GAMS (general algebraic modelling language, www.gams.com). The interested reader is referred to Mavrotas (2007, 2009) for further details of the AUGMECON method.

Using GAMS, the outcome of the model shows three optimal alternatives taking the expected or observed mass balance into account (see section 5.5). The computing time to solve the MOMILP is 22 seconds. Solving the alternatives α_2, α_3 and α_4 separately, as MoLP models using Matlab R2014b, validated the model results. In general, such MoLP models have no single solution but a set of Pareto-optimal solutions. Only in the particular case of non-conflicting objectives will the outcome be a single optimum solution (Deb, 2009). Since equations (26) and (27) do not conflict and since objective Z_3 is not a function of Δp, Δs and Δc, the individual MoLP for each alternative can be solved as an LP model, considering the objectives Z_1 and Z_2 separately as a single objective function. The solutions for each individual LP model will be the same, regardless of whether Z_1 or Z_2 is used as the objective function.

As a result of solving the MOMILP, GAMS generate different optimal parameter solutions for each alternative (Δp, Δs and Δc). Following Deb (2009), the optimum objective values of each alternative constructs the elements of the ideal-point vector for the global problem under investigation. Finally, each single optimal solution per alternative is weighted and is allocated a weighted per cent of deviation factor, *WPD*. This is a measure that calculates the weighted distance between an optimal solution and the ideal point. Each objective function gets a weighting factor, w_j, representing its importance. For all solutions s of the Pareto-optimal set, the value f_j^s of the j^{th} objective function is calculated and compared with the ideal point of the j^{th} objective function value f_j^*. The ideal point is formed by the optimal result per objective function over all the assessed alternatives. The values of the ideal point are marked in bold in Tables 7 and 8 of section 5.5.

$$WPD_s = \sum_{j=1}^{3} \left[w_j \cdot \frac{\left| f_j^s - f_j^* \right|}{f_j^*} \right] \qquad (41)$$

5.5. Scenario analysis

In this section we discuss the outcome of the model described in the previous subsection.

In general, sustainable recovery of biomass waste requires subsidies in order to be economically viable. These subsidies can differ greatly across European member states and regions. In the neighbouring countries of Germany, the Netherlands, and the UK, such subsidies are substantially higher than in Flanders (OVAM, 2009). Basically, two forms of subsidies are used to support the introduction of sustainable use of biomass recovery investments: those granted for investments, or those granted to support exploitation. Some European member states, or regions, employ both forms of subsidy; others employ only one. In Flanders both types of subsidy are in place (OVAM, 2009).

Another notable difference is the link between subsidies and the waste conversion method. Some EU member states or regions support more environmental use of biomass through higher subsidies; as a result these (novel) conversion methods are being applied in spite of their higher (initial) investment cost (OVAM, 2009).

In our experiments we consider two scenarios: one with no subsidy being granted and one with a subsidy to separate the cuttings from an incoming green waste batch. In the latter case, a subsidy *S* [€] will be subtracted from the net Fixed Capital Investment cost, *FCI*.

Scenario 1: no subsidies

The first scenario represents the current situation in Flanders where no subsidies are granted for the separation of the wooden fraction of biomass from green waste for waste-to-energy purposes. This is the situation described in Section 4. The optimal solutions for the four alternatives are expressed in Table 7 for the expected mass balance and in Table 8 for the observed mass balance. The optimum objective values forming the ideal-point vector are indicated in bold.

Alternative *k*	Δp [ton]	Δc [ton]	Δs [ton]	Z_1 [€]	Z_2 [LCA pt]	Z_3
α_1	0	0	0	0	0	0.26
α_2	0	-1875	3750	**30750**	-11919375	0.14
α_3	5000	-1437.5	1875	-10375	**-38776190**	0.28
α_4	5000	-500	0	-25750	-32816500	**0.32**

Table 7: Outcome of the mathematical model for the four alternatives under study (expected values)

Alternative *k*	Δp [ton]	Δc [ton]	Δs [ton]	Z_1 [€]	Z_2 [LCA pt]	Z_3
α_1	0	0	0	0	0	0.26
α_2	0	-2066	3750	**26829**	-11625420	0.14
α_3	5000	-2938	1875	-41128	**-36469919**	0.28
α_4	5000	-1905	0	-54553	-30657020	**0.32**

Table 8: Outcome of the mathematical model for the four alternatives under study (observed values)

The best solution is the one with the overall lowest relative deviation to the optimal solution expressed by the WPD_s factor. The WPD_s is calculated for the four alternatives for four different weighting factor combinations w_1, w_2 and w_3 representing: strong emphasis on profit (w_1=0.8, w_2=0.1 and w_3=0.1), medium emphasis on profit (w_1=0.6, w_2=0.2 and w_3=0.2), emphasis on profit and environment (w_1=0.4, w_2=0.4 and w_3=0.2), and equal emphasis on profit, environment and social wellbeing (w_1=0.33, w_2=0.33 and w_3=0.33). The results are depicted in Figure 4 for the expected mass balance and in Figure 5 for the observed mass balance.

The solution with the lowest WPD_s value is the optimal solution for the multiple objective-programming model. In the scenario without subsidies, the optimal situation is the second alternative (i.e. only partial separation of the sieve overflow for which no investments have to take place), independent of the use of the expected or observed mass balance and independent of the weight factors assigned to the components Profit (w_1) –Planet (w_2) -People (w_3).

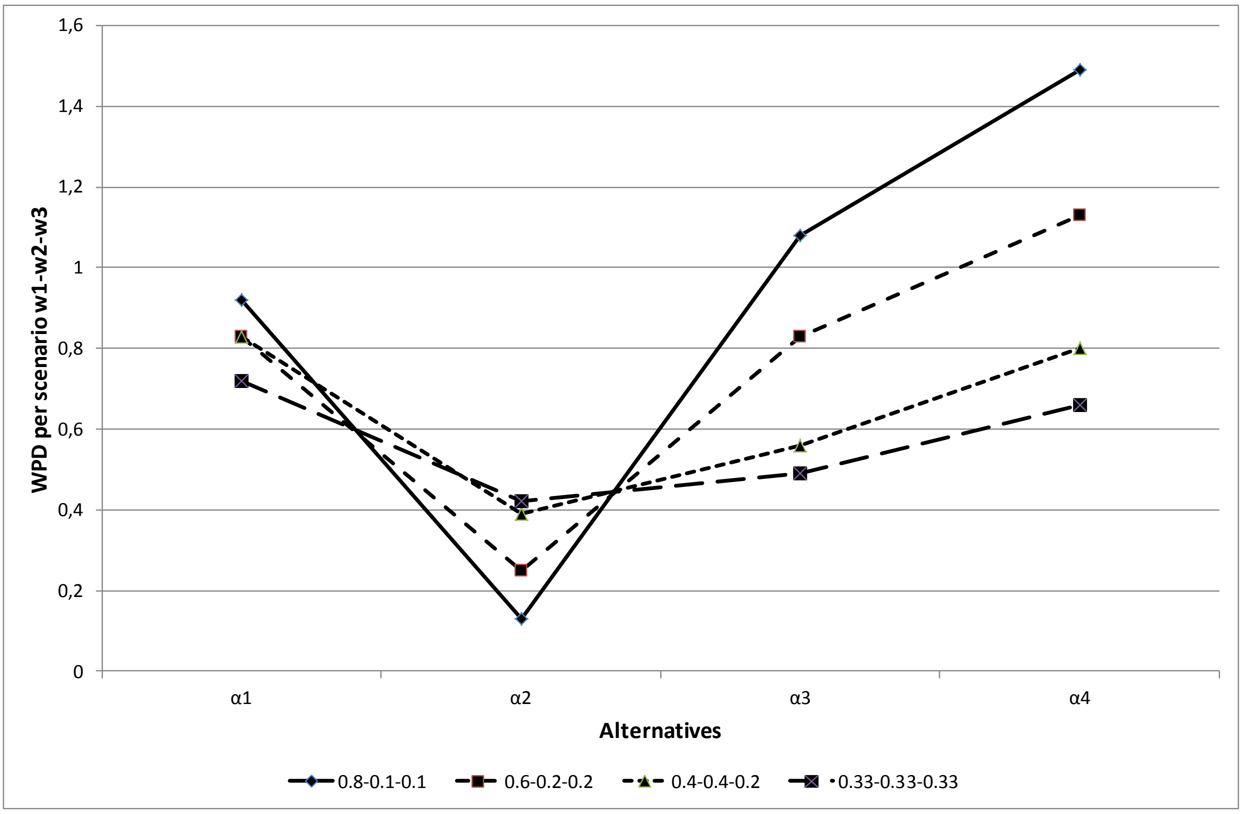

Figure 4: Expected mass balance overview WPD values for different values of weight factors w_1-w_2-w_3

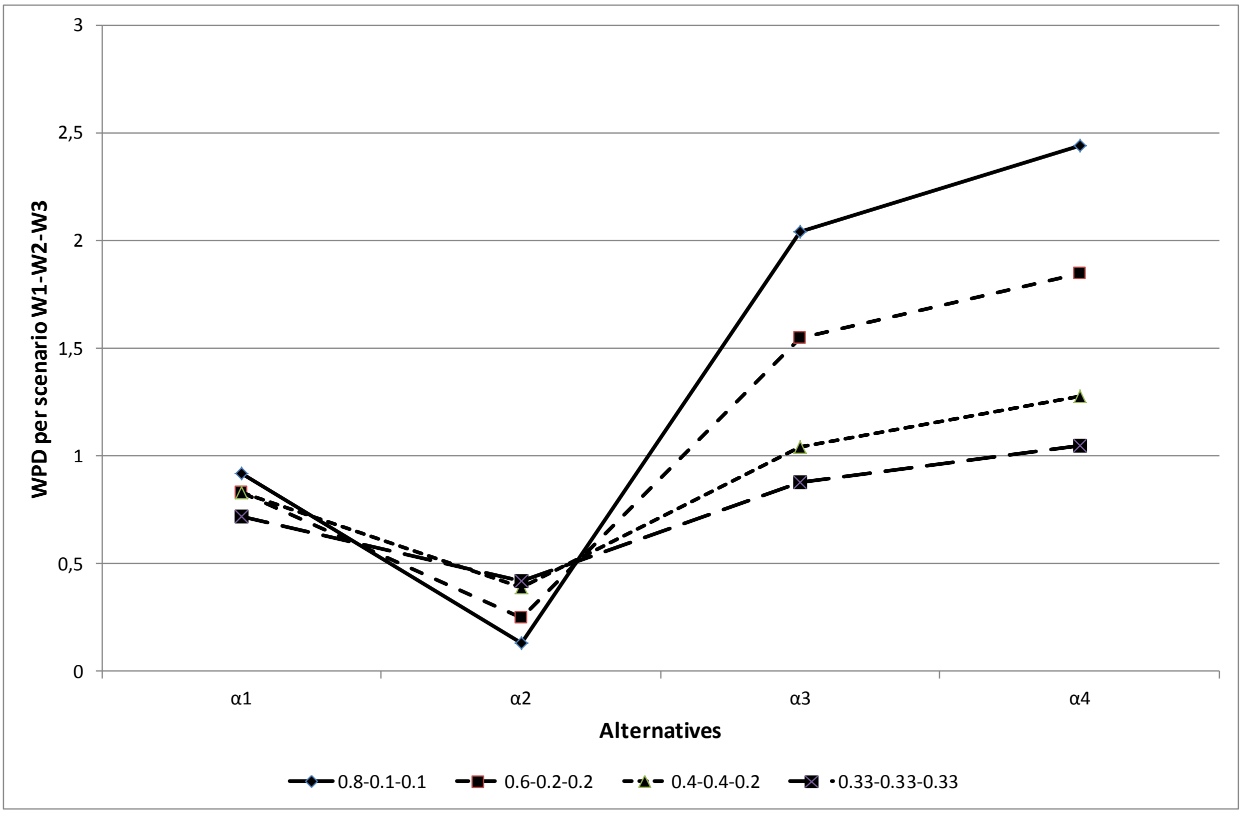

Figure 5: Observed mass balance overview WPD values for different values of weight factors w_1-w_2-w_3

Scenario 2: Investment subsidy for pre-treatment

If a subsidy of *S* [€] for investment in pre-treatment is granted, the optimal alternative will differ depending on the size of the subsidy and the weights assigned to People-Planet-Profit (Figures 6, 7 and 8). The tipping point for alternative α_3 to become the optimal alternative instead of alternative α_2 is dependent on the assigned weighting factors to People-Planet-Profit. We demonstrate this effect for the case of the expected mass balance. If w_1=w_2=w_3=0.33, the tipping point to shift from alternative α_2 to α_3 as the optimal alternative is a subsidy equal to *S*= 5,637€. If w_1=0.8 and w_2=w_3=0.1 then the tipping point is *S*=36,443€ and if w_1=w_2=0.4 and w_3=0.2 then the tipping point is *S*=13,581€. For all alternatives—except for the reference situation of alternative α_1—granting a subsidy *S* [€] has an impact on the relative optimization of the alternatives α_2, α_3 and α_4. We observe that the higher the subsidy above the tipping point, the less attractive alternative α_2 becomes compared to the alternatives α_3 and α_4 (see Figures 6, 7 and 8).

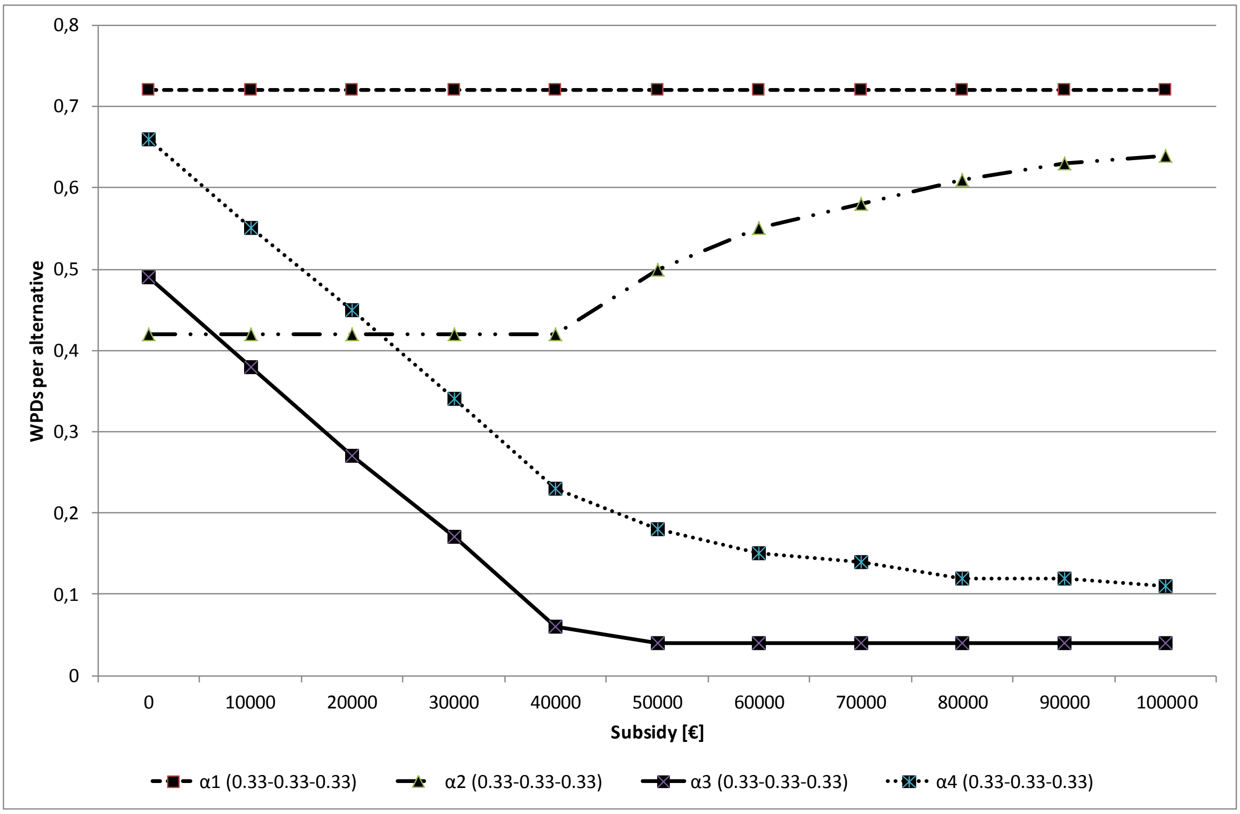

Figure 6: Influence of a subsidy *S*[€] on the optimal alternative selection for w_1=w_2=w_3=0.33

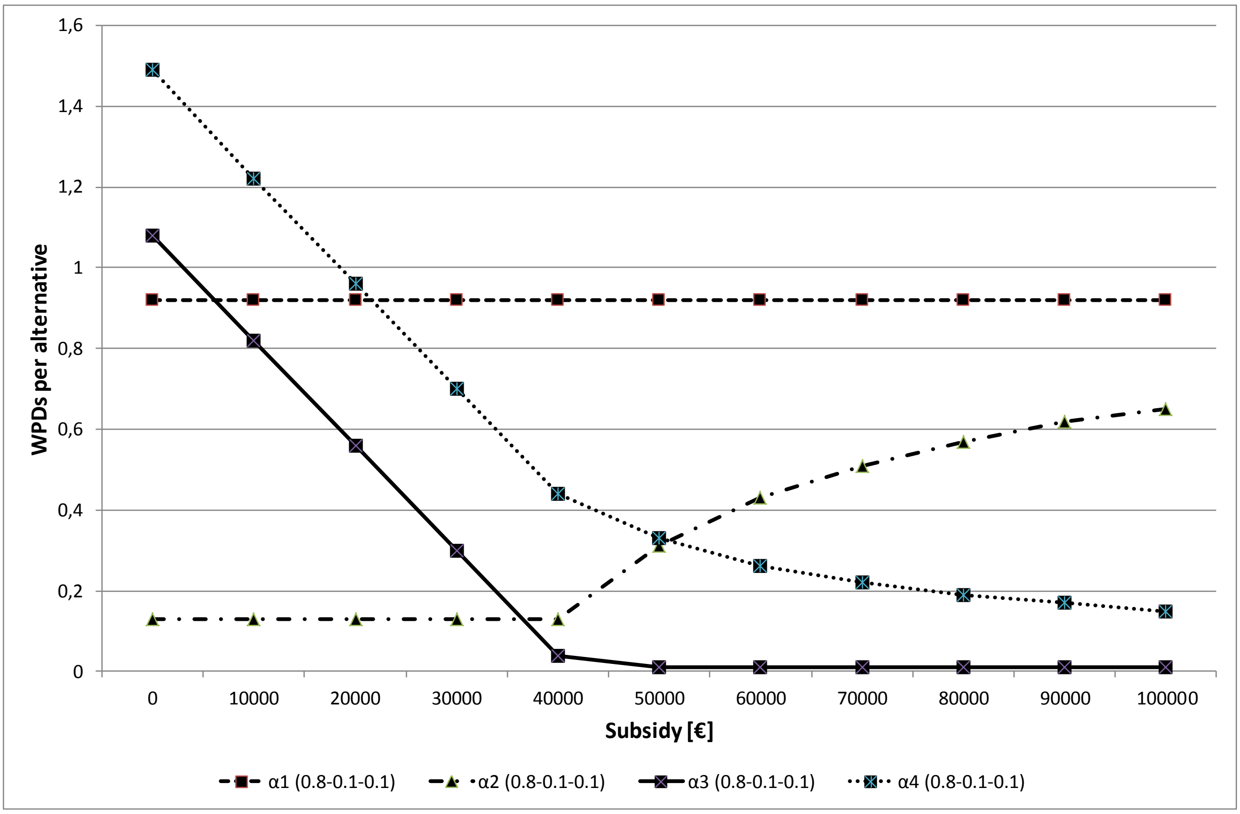

Figure 7: Influence of a subsidy *S*[€] on the optimal alternative selection for w_1=0.8; w_2=w_3=0.1

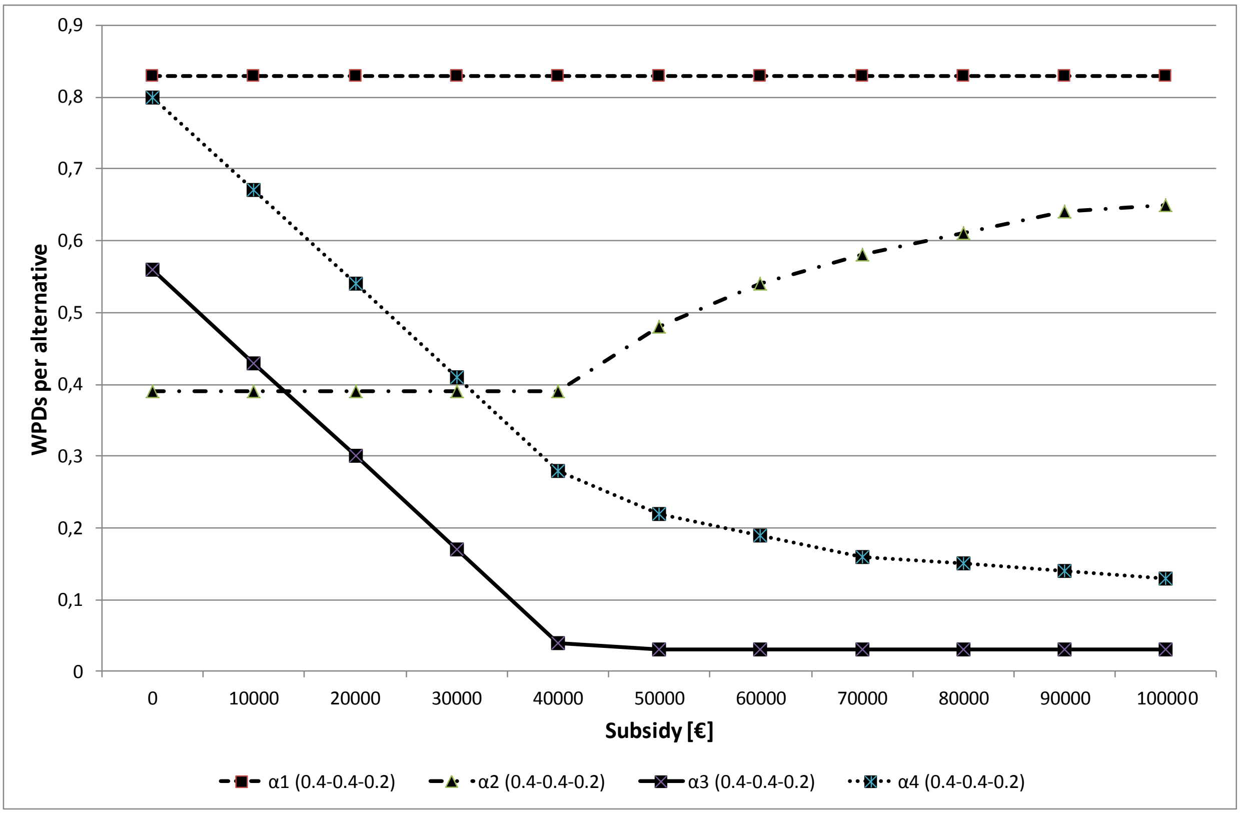

Figure 8: Influence of a subsidy *S*[€] on the optimal alternative selection for w_1=w_2=0.4; w_3=0.2

6. Conclusions on research findings and directions for further research

The use of renewable energy sources is becoming increasingly important to mitigate the impact of global warming. In Europe, biomass is the most commonly used renewable energy source; however, biomass extracted from waste flows is still an undervalued feedstock (Gold and Seuring, 2011). This paper assessed whether separating sieve overflow and/or fresh woodcuttings from green waste to be used for energy production could be more sustainable than exclusive green waste composting. Assuming this could be demonstrated and that the separated quantity of sieve overflow and cuttings does not hamper the composting process, a portion of the wooden fraction of green waste could be used as biomass feedstock for energy valorisation in compliance with the European Waste Directive 2009/28/EC.

To answer this research question, a multi-objective mixed-integer linear programming model that takes the three pillars of sustainability into account was formulated and solved using the ε- constraint method. This paper contributes to the scarce literature on simultaneously optimizing the three sustainability pillars as well as to valorisation of undervalued waste streams for the sustainable production of power and heat.

The model was applied to green waste test data of OVAM, the public Flemish Waste Agency. Model outcomes show that the optimal alternative depends on the level of available subsidies. If no subsidies for separating cuttings prior to composting are granted, the alternative of separating a part of the sieve overflow for energy valorisation is a better alternative than the reference situation in which all green waste is used exclusively for composting. If a sufficiently large subsidy is granted, the optimal valorisation alternative shifts to partially separating fresh cuttings in the incoming batch of green waste and partially separating the sieve overflow, with both used for energy valorisation. The model outcome supports earlier expectations of OVAM that retrieval of some wooden mass out of green waste would lead to a better sustainable result. However, compared to the solely economic evaluation of the four alternatives, sustainability optimization presents a nuanced picture in which other alternatives can be preferred depending on the policy choice assigned to the importance of the People-Planet-Profit indicators.

The framework presented in this paper also can be used to assess recovery processes for other types of waste and biomass. Because the methodology is capable of comparing alternative processing and recovery methods using the triple bottom line concept, it can help decision makers identify trade-offs between three basically incommensurable dimensions. Further research could be directed towards including additional sustainability dimensions (following e.g. Munda, 2005) and examining the weighing criteria for the sustainability dimensions in order to gain greater insight into the sensitivity of model outcomes. Additionally the proposed framework could be used to determine the amount of subsidy that would be required to make currently economically unviable pre-treatment and recovery processes such as pyrolysis attractive.

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